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Creating an optimal portfolio with covariance adjustments for moving average trends

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CREATING AN OPTIMAL PORTFOLIO WITH COVARIANCE ADJUSTMENTS FOR MOVING AVERAGE TRENDS

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Introduction

Whether deciding where to invest the capital of a large corporation, or managing your own financial accounts, the goal is to invest in assets in a way that best benefits the owner of the portfolio. There are many assets to choose from and each comes with their own large set of unique characteristics. Some characteristics are important in creating the best possible portfolio, some are not, and some are still hotly contested by financial practitioners. Among the unique characteristics, two are undisputed in regards to their importance of circles forming the best possible portfolio: return and volatility, more commonly known as the reward and the risk, respectively.

The return of an asset is considered to be the percentage gain an investor has received from the sale of an asset. If you invest 100 dollars in a portfolio today and sell it for 150 dollars tomorrow, you have made 50 dollars over your original purchase, or a 50% return (50 divided by 100). But one does not know if a portfolio is going to be worth more tomorrow than it is today. Consequently, without any information on how the stock has performed in the past, or reasons it should perform well in the future, it can be difficult to predict whether one should invest into a particular portfolio or not. To overcome this issue, investors commonly assume that the average of historical returns are an accurate estimate of what that portfolio would return in the future, on average. The return of an asset is the primary reason one gives up their money rather than spend it on themselves. The return is the reward for having sacrificed instant gratification for the longer-term benefits that come from allocating money to whatever the investment is. The reward isn't always guaranteed. Rather, by all appearances this reward is random. If you look at any graph showing historical stock portfolio prices, you will see that portfolios rarely achieve the same return going forward on a consistent basis. In fact, they often do the opposite, reaching significant highs and lows in comparison to the expected mean. This is where the second, widely used statistic, volatility comes into play in the creation of a superior portfolio.

Volatility explains how far away from the expected mean the price of the portfolio is likely to go, a characteristic that is measured by standard deviation. A portfolio with a high standard deviation is much more likely to be significantly higher or lower than the average, whereas a portfolio with a lower standard deviation will tend to be closer to the average. This measurement helps give the investor a better understanding of the likelihood and magnitude of a downward price change in a portfolio. It is for this reason volatility is considered the risk of an investment. Volatility on its own, like the return, cannot predict the long-term success of an investment because, without knowing from what return it is moving from, the asset could have low volatility but be moving around a negative return. This is why it is important to examine how both volatility and return work together: risk versus reward.

In order to be able to evaluate the risk-reward efficiency of a portfolio, the finance industry has adopted a ratio devised to universally measure the optimality of any portfolio. This measure has been called the Sharpe ratio, conveniently named after the Nobel Price Winning economist William F. Sharpe (Bodi et al., 2018). Consider two portfolios: Portfolio A has an expected return of 15 percent and a standard deviation of three percent, Portfolio B has an expected return of 40, but a standard deviation of ten. It can be difficult to discern which portfolio is the better option. The Sharpe ratio is an easy calculation that explains how much reward you are expecting to get for each unit of risk you are undertaking. Simply stated, it is the expected return divided by the standard deviation. When looking at the two portfolios given above, “A” and “B”, the Sharpe ratios are five and four, respectively. This shows that Portfolio A will give you the most reward for the risk you undertake, despite Portfolio B having the greater potential reward (i.e., 40%). Because of its ability to evaluate assets with varying returns and volatility, the Sharpe ratio has become one of the leading tools for evaluating a portfolios effectiveness. The best, also referred to as “optimal,” portfolio is one of all possible portfolios that has the highest return over volatility.

All of the calculations above are looking at portfolios as if they are a single asset, when realistically, a portfolio is made up of five, ten, thirty, or even hundreds and thousands of different assets. Each asset has its own measurement of returns and volatilities, but in a portfolio, it is also important to recognize how these assets relate together, specifically their volatilities. Understanding the way assets correlate with each other helps explain why “diversifying your portfolio” is such a common phrase when creating an optimal portfolio. When adding a second asset to a portfolio, finding the return of the portfolio is done by taking the average of the returns of the two assets in the portfolio (Bodi et al., 2018). The volatility is not as simple. One characteristic of portfolios is that the volatility of the portfolio is less than at least one of the assets contained in the portfolio. This effect happens as a result of the assets’ returns canceling each other out. If one asset returns ten percent over its expected return and the other returns thirty percent over its expected return, the portfolio itself performs twenty percent over the expected return. Some scenarios involve an asset having a negative return while the other has a positive and the returns cancel each other out (Bodi et al., 2018). Covariance does not always decrease volatility, but in these two situations, the canceling out and mitigating asset variation, lowers the volatility of a portfolio dramatically while still conserving the average of the expected returns of a portfolio. Because of its potential to decrease volatility, without affecting the returns, covariance becomes a center piece in the creation of an optimal portfolio through a process called mean-variance optimization.

Mean-variance optimization, a process first highlighted by Sharpe and Markowitz finds the allocations among a pool of assets that results in a portfolio having the highest possible Sharpe Ratio; that is, a portfolio that is Optimal (Bodi et al., 2018). To find these allocations, Mean-variance optimization relies on the historical covariances and the expected returns among the pool of potential assets the investor is considering. Pitfalls of mean-variance optimization are many. For example, this method operates under the assumption that the assets expected returns can be predicted by how it has performed in the past (Bodi et al., 2018). Additionally, the way two assets' returns relate, through covariance, is also assumed to be what they were in the past. Although mean-variance optimization is more than capable of finding, in hindsight, which asset allocation would have proved optimal, the idea of historic data predicting future results leads to skepticism in the financial analyst community.

Because of the skepticism of the predicting power of historical data, the finance community is split into two groups: group one believes that technical analysis, the use of historic prices and sales volume, can be used to predict future data (Kirtzman et al., 2010). Conversley, group two believes that stock prices are too complicated to predict and resort to a portfolio that does not rely on this information and instead relies on diversification alone. Although they disagree on the use of technical analysis, they both agree with the power of diversification in a portfolio and insist that a well-diversified portfolio is key to creating an optimal portfolio. Technical analysis research has shown promise in different methods to weight their portfolios, one of which is trend analysis.

Trend analysis attempts to use the historic movement of stock prices to accurately predict if future movement of the stock price will be positive or negative. Despite speculation of technical analysis, this method has proven to show better than average portfolio returns in comparison to raw market returns (Han et al., 2013). Occurances like this spur investigation into other ideas which might prove to be the next strategy to create an even more optimal portfolio. Mean-variance optimization and trend analysis are both methods which have proven capable of creating an optimal portfolio on their own, and financial practitioners appear to view these as separate approaches to portfolio formation (Bodi et al., 2018).

In this analysis, I investigate whether combining these two traditional methods of portfolio construction, mean-variance optimization and trend following, enhance the performance of a portfolio. Specifically, I consider whether stock trends within a pool of stock mechanically influences the covariance matrix for this pool of assets – a crucial input for mean-variance optimization. I then use these trend modified covariances to form a new mean-variance optimized portfolio and then evaluate performance. Instead of using the trends to determine whether or not to invest in a stock, as trend analysis postulates, I will be using trends to create new covariances between assets that better capture the essence of how two assets relate. These new covariances, instead of being only historically based, will be based on historic covariance only in days which match the prevailing trend of each asset. The results of this investigation will bring about more understanding of optimal portfolios and the factors that affect their creation.

Literature Review

Whether or not stock information such as price changes, historical returns, sector volume, and other technical information can be used to create a portfolio that outperforms more elementary methods of portfolio construction is a hotly contested topic within financial analyst spheres (Farias Nazário et al., 2017). The purpose of this research is to outline a potential method of portfolio development that has not been previously examined. This method combines the use of a trend analysis with a Markowitz model, creating a new composition of covariance matrices between the assets – a focal point of the mean-variance optimization approach. The effectiveness of this model was tested against the benchmark 1/N Naïve portfolio, a standard Markowitz portfolio, and a trend portfolio. The tool for evaluating the success or failure of the strategy was the Sharpe ratio.

Sharpe Ratio

One of the goals of any rational investor is to try and gain the highest level of return given an amount of risk, or vice versa, take the lowest amount of risk for any given level of return. Investments in the stock market (the assets utilized in this study) have varying risks ranging from idiosyncratic (business) risk to systematic (market) risk. One of the most common ways to evaluate the “riskiness” of an asset is to look at the asset’s return fluctuations over time and compare those fluctuations with the average return of that time period to get the standard deviation.

$$S_i = \frac{Er_i}{\theta}$$

To calculate the Sharpe ratio, take the average return of the asset and divide it by the standard deviation. This effectively shows the expected percentage return for a single percentage of standard deviation (Bodi et al., 2018).

Naïve 1/N Portfolio

The 1/N portfolio is considered a standard benchmark for any analysis investigating the returns of a portfolio creation strategy attempting to have a high Sharpe ratio. The reason for this is that the 1/N portfolio, with a simple design, also manages to be difficult to outperform with alternative strategies when conducted out of sample. The 1/N portfolio invests an equal weighting into each asset within the portfolio. After the assets are purchased in equal weighting, they are held until the end of a predetermined, unchanging period of time (monthly, quarterly, annually). At the end of the period, the portfolio is rebalanced, meaning each asset is either sold or purchased until the value of each is equal (Curran & Zalla, 2020). The 1/N strategy rebalances each period to equal weighting meaning if there are two assets, each would be invested into with one-half of the capital; if there are three, each would get one-third, hence 1/N. This does not take into consideration the history of returns, fluctuations in the market, the relationship of assets to each other, or any other possible information that could be derived from historical or current information regarding the assets included.

With all of the information available, why does this portfolio perform well when compared to other strategies? Inherently, due to the structure of the strategy, you avoid placing a significant amount of capital within a singular asset. There would never be a situation where you have 80% of your capital within one asset at the beginning of the period. Another reason the 1/N portfolio performs would be the strategy naturally requires you to buy low and sell high. At the end of the period, any asset you have which has gone down in value was purchased, while any asset that has appreciated in that time period was sold until the assets are weighted equal in value.

Although the 1/N portfolio has its merits, it also has its faults. A study conducted by Kritzman, Page, and Turkington (2010) offered a deep investigation into what they call “The Defense of Optimization: The Fallacy of 1/N”. In this study they investigate strengths and weaknesses of the 1/N portfolio, explain why many optimization attempts fail to outperform the 1/N portfolio, and create a framework for some ways to achieve higher returns based on the risk taken. Although 1/N avoids heavily weighted positions, and mechanically buys assets at a low price and sells assets at a high price, it neglects information we may have about the asset such as expected risk and return (Kirtzman et al., 2010). Kritzman et al. (2010) postulated that the failure to create a more optimal portfolio is not due to error maximization and instead due to uninformed calculations of expected returns and variances. When using alternative methods outside of small historical samples, methods outside of the 1/N portfolio are more than capable of being high performers. The 1/N portfolio, with minimal research or information required to utilize it, becomes a benchmark for further investigation into creating a more optimal portfolio.

Trend Portfolio

The price trend of an asset is measured by the change in the positive/negative sign of the difference between the 50 day moving average price and the 200 day (Flugum, 2020). The Trend Portfolio utilizes the 1/N portfolio idea, but at the end of each period and at the start of the portfolio, rather than rebalancing each asset to be equally weighted, only assets in a positive trend were equally weighted. For example assume there are six assets. If two are in a negative trend, and four are in a positive trend at the end of the period, then the two assets were sold, and the remaining four assets were each invested equally weighted.

The thought behind this strategy, supported in a research paper written by Han, Huang, and Zhou, is that a stock in a positive trend is thought to be on the path of continued stock price appreciation, whereas a stock in a negative trend would be expected to continue declining. Trends take the moving average price of a short period of time and compare it the average price of an extended period of time. If the average price over the short period of time is greater than the moving average price of the long period of time, then the trend is positive signaling that the current return is higher recently than it has been over the longer run, vice versa (Han et al., 2013). This allows insight as to whether returns can be expected to be positive in the future.

Within the trend portfolio, there is no consideration for how the stocks prices correlate with each other. This can potentially create situations of highly weighted assets correlated with each other taking sudden downturns at the same time. The study by Han, Huang, and Zhou (2013) show the positive effects of using the moving averages on returns, but the purpose of this study is to examine the possibility that the moving average trends potentially have an impact on the covariance and, therefore a potential opportunity for mean-variance optimization.

Markowitz Portfolio (Traditional Mean-Variance Portfolio)

The Markowitz Portfolio works around the understanding that the way two stocks move in relation to each other is a factor capable of being calculated and used in creating a portfolio with the lowest risk for a given return through mean-variance optimization. Understanding this allows for efficiency in diversification when deciding the weights in the assets involved to construct a portfolio with the highest possible Sharpe ratio. This is operating under the assumption that the covariance is solely dependent on the historical returns of the assets. These historical returns may be based off of one month, one year, or the entirety of the lifetime of the stock, each of these represents a potentially different covariance resulting in different potential optimal portfolios (Bodi et al., 2018). Because the covariances are based on only historical data there could be potential for better methods for predicting covariances.

Recent Work on Different Mean-Variance Portfolios

Recently, Curran and Zalla (2020) investigated multiple portfolio development strategies utilizing various volatility estimation models. Within their study, they took six datasets often used by financial analysts in the financial industry such as Fama-French Portfolios, industry organized portfolios, and momentum sorted portfolios to name a few. They took each of these different datasets, used 14 econometric models for estimating each asset's expected returns, then used four different optimal portfolio development strategies in order to determine the weighting of the assets in the portfolio: Minimum-Variance Portfolio, Constrained Minimum-Variance Portfolio, Volatility-Timing Portfolio, and Tangency Portfolio. The effectiveness of these Econometric models and optimal portfolio constructions were measured based on the percent difference of the Naïve 1/N portfolio's Sharpe ratio, Sharpe ratio net of turnover costs, and volatility (Curran & Zalla, 2020). My study, although inspired by some methods they used, was more of a baseline, proof-of-concept research paper.

This Study

In this study, I use technical trading strategies focusing on the positive/negative trends of six different assets in order to create a new covariance matrix to be used in deciding the asset weights for yearly rebalancing. This is a new take on different volatility measurements used in the past, and may prove to provide Sharpe ratios exceeding the Naïve portfolio as well as just using trend analysis alone to rebalance a portfolio. Analyses have been done on the effectiveness of moving average portfolios with success, however these portfolios fail to account for potential changes in covariance, which can be used for better optimization. In depth studies, as described above, have also shown the impact of utilizing four different mean-variance optimization strategies, each with success, but none examining the effect that trend analysis potentially has regarding the covariance matrix of a portfolio of assets. This study examines this possibility and should add a new take on trend analysis and its use in creating a covariance matrix.

Hypotheses to Be Tested

Hypothesis I

If one of two stocks changes its moving average trend, then the covariance between the two stocks will be significantly altered,

Hypothesis II

If I utilize the altered covariances in a mean-variance portfolio, then the portfolio will achieve better performance over time than the 1/N portfolio, trend portfolio, and the 1/N Markowitz portfolio.

Methodology

Raw Data and Characteristics

Following Zalla and Curran (2020), I sought to evaluate the usefulness of different methods of determining the assets' covariances. It was important to test the new portfolio against multiple types of datasets to truly see where this method was applicable and used different types of econometrics when estimating expected returns to build a full picture of our results. That being said, with software restraints, the trend covariance method was only to be tested with a few commonly utilized index funds for a potential proof of concept. The current index funds to be tested in a portfolio together are SPY, IWM, QQQ, AGG, GLD, and VNQ. In order to keep the information relatively current, but also have a sufficient amount of data, daily stock prices from 2009-2019 were utilized; analysis was done on each year individually.

Returns were calculated for each of the six assets on a monthly basis from January 2009 to December 2019 by taking the difference of price at the end of the current month and the price at the end of the preceding month, and dividing by the price at the end of the previous month.

Formula can be expressed by:

$$r_{i,t} = \frac{p_{i,t} - p_{i,t-1}}{p_{i,t-1}}$$

Where p is the price of the asset, t is the month the price was taken, and r_i is the assets return. The raw return was required before being able to find the raw standard deviation, which was being used as the portfolio's volatility measurement.

Because the investigation was examining four portfolios rebalancing at yearly intervals, the covariances were calculated to correspond with the yearly periods to help in determining the weights of each of the portfolios when rebalancing. The way in which the raw covariance was calculated was by taking sumproduct of each of asset x's historical daily return difference from x's mean return of the year and each of asset y's historical daily return difference from y's mean return. This sumproduct was then divided by the number of days observed minus one. Also expressed as:

$$cov_{x,y} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{n - 1}$$

Where x_i is the assets price on a specific day and $\bar{x}$ is the average price, the same for y_i and $\bar{y}$, and n is the number of days observed for the calculation. This was done for the relationship of each asset to each other asset (SPY with IWM, QQQ, AGG, GLD, and VNQ, then IWM with QQQ, AGG, GLD, and VNQ, etc.) in order to construct a matrix to be used for the Traditional and Trend Mean-Variance Portfolios. A separate matrix was constructed for each of the years from 2009 to 2019. For each year, all historical data starting from 2009 to the respective year was used to calculate the covariances between each asset. For example, the construction of the 2011 covariance for each asset relationship was calculated by using the returns from the beginning of 2009 to the end of 2011.

Daily Trend Analysis

In order to construct the Trend and Trend Mean-Variance portfolios, I have to find, at each day, whether each stock was in a positive or negative trend. At the end of each year, how the portfolio rebalanced was determined by each assets trend in the trend portfolio. In the Trend Mean-Variance portfolio, the daily trend was used in the construction of the covariance matrix. The method used to calculate the trend was to take the difference between the 50 day price moving average (the average of the price over the preceeding 50 days) and the 200 day price moving average (the average of the price over the preceeding 200 days). The days counted were 50 days in which the stock market was open because these were the days the assets were actively traded, and this was the method used in the trend analysis studies by (Han et al., 2019). Any day where the difference of the 50 day moving average and the 200 day was greater than zero it was marked to be in a positive trend that day. If the difference was less than zero it was marked to be in a negative trend.

Trend Adjusted Covariance Matrix

The same method used to construct the raw covariance matrix was used for the trend adjusted covariance matrix with one key difference. Instead of using all of the historical daily returns, the historical returns of only the days in which the two assets shared the same trend as they did at the end of the year were used in the covariance calculation. For example, if SPY at the end of 2010 was in a positive trend and QQQ was in a negative trend, the 2010 trend adjusted covariance was calculated using the returns of any date in which both SPY was in a positive trend and QQQ was in a negative trend. In this example, any day where SPY was in a negative trend, or QQQ was in a positive trend, was filtered out of the calculation.

I decided to use a t-test on the difference between the raw covariance and the trend adjusted covariance to test the significance of the change in the covariance. The T-test was used to analyse each asset relationship, show I calculated a T-Test for the difference in covariance for SPY and QQQ as well as SPY and GLD etc.

Portfolio Construction

All of the portfolios were constructed following similar rules. (1) Historical monthy returns were used to calculate the value of the assets within the portfolio during the year to keep calculations simple. (2) Each portfolio rebalances at the end of each year following the rules of the specific to the portfolio. (3) Each portfolio begins with $10,000 invested into the portfolio. (4) All earnings are reinvested into the portfolio when rebalanced.

The Naïve Portfolio was relatively simple to construct in comparison to the creation of the other portfolios which is one of the reasons why it is so practical. The portfolio was constructed by investing one sixth of $10,000 into each of the assets at the beginning of the portfolio and allow that dollar to rise and fall with the asset’s return as shown by the historical data. At the end of each year, the assets are either invested into or divested out of in order to bring each of the assets to be equally weighted. Monthly returns were used instead of daily returns to keep calculations simple however, this does have an impact on the volatility calculated of the portfolio.

Constructing the Trend Portfolio also was not difficult because the method of rebalancing was practical, similar to the Naïve Portfolio. The portfolio was constructed by investing $10,000 at the beginning of the portfolio, divided equally into stocks which were in a positive trend at the end of the previous year according to the trend calculations. At the end of each year, the assets are either invested into or divested out of to rebalance the assets so that the assets which are in a positive trend are invested into by equal amounts.

Both Mean-Variance Portfolios were more tedious to construct in comparison to the others. In order to figure out the weighting of each of the assets in the portfolio each year, the raw covariance matrix and the historical returns calculated for the prior years were used to figure out what asset weighting would have brought about the highest Sharpe ratio. This calculated asset weighting was then used as the weighting of each asset in the portfolio to be evaluated in the following year. For example, the allocation weighting calculated as having the best Sharpe ratio for 2009 would be used for 2010. This same process was used in the Trend Mean-Variance Portfolio, but instead of using the raw covariance matrix, the trend covariance was used instead.

Even though a portfolio may show higher than normal returns, it was important to be able to identify whether or not those returns differ from other methods in a statistically significant way. Often used to evaluate the statistical significance of a portfolio creation method, I used the Fama-French three factor model to evaluate the abnormal performance of each strategy. Specifically, I regressed the monthly time-series of returns for each strategy onto the the three factors of the Fama-French 3 factor model. I then used the estimated intercept of the FF model to assess perfromacne among the strategy portfolios. (Somethig along these lines).

Results

The results of this analysis showed when adjusted to account for the trend at the end of the year, the change in covariance, as well as the portfolio it creates, were statistically insignificant. The results show the portfolio to receive the highest return over the ten year span was the Naïve portfolio ending the period with over $27,500 followed by the Trend Mean-Variance and Traditional Mean-Variance portfolios with $18,700 and $18,400 respecively. The Trend portfolio severely underperformed with its ending value being less than where each began, ending at $9,100. The most optimal portfolio with the highest Sharpe ratio was the Traditional Mean-Variance portfolio with 0.52% return for each percent of standard deviation followed by the Naïve and Trend Mean-Variance portfolios with 0.33% and 0.25% respectively. The Trend portfolio again underperforms with 0.01% return for each percent of standard deviation.

The differences found in the covariance were of varying statistical significant with most of the asset relationships being deemed statistically insignificant. There are, however, a couple of relationships which did have statistically significant differences between the traditional covariance and the adjusted covariance. For example, in Figure 1, the T-test shows, for the VNQ, QQQ relationship, there was in fact a statistical significance with a value of

3.44. The rest of the relationships however fail to meet a 5% confidence interval in saying the difference was statistically significant.

	SPY	IWM	QQQ	AGG	GLD	VNQ
SPY	1.53					
IWM	0.85	0.34				
QQQ	1.46	1.48	0.48			
AGG	-0.70	0.04	0.01	0.25		
GLD	-0.79	-0.63	-0.25	-1.54	-0.43	
VNQ	1.18	1.12	3.44	-0.55	-1.50	0.21

Figure 1 Adj. Covariance Difference T-Test

A practical way to show the returns of a portfolio over time was by charting out how the value of $10,000 grows over the lifetime of the portfolio. The returns of each of the analyzed portfolios can be examined in this manner in Figure 2. In Figure 2, the Naïve portfolio and the Trend Mean-Variance portfolio take the lead for the first couple of years. However, after 2013, the Trend Mean-Variance portfolio loses pass with the Naïve portfolio and begins to converge with the Traditional Mean-Variance portfolio. One thing to note is the smoothness of the two mean-variance portfolios in comparison to the volatile Naïve portfolio. The Trend portfolio failed to perform as well as expected and the reasoning is discussed in the areas for improvement section.

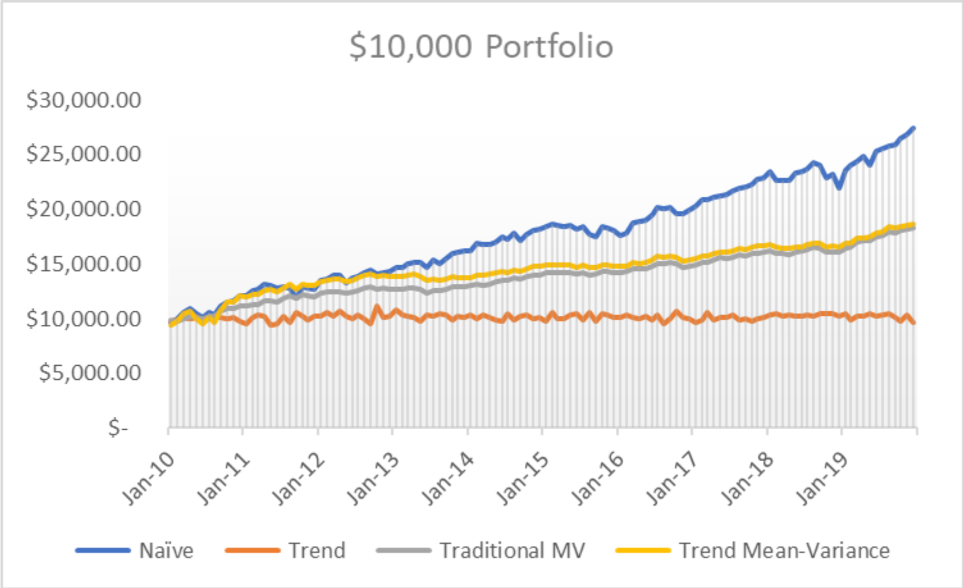
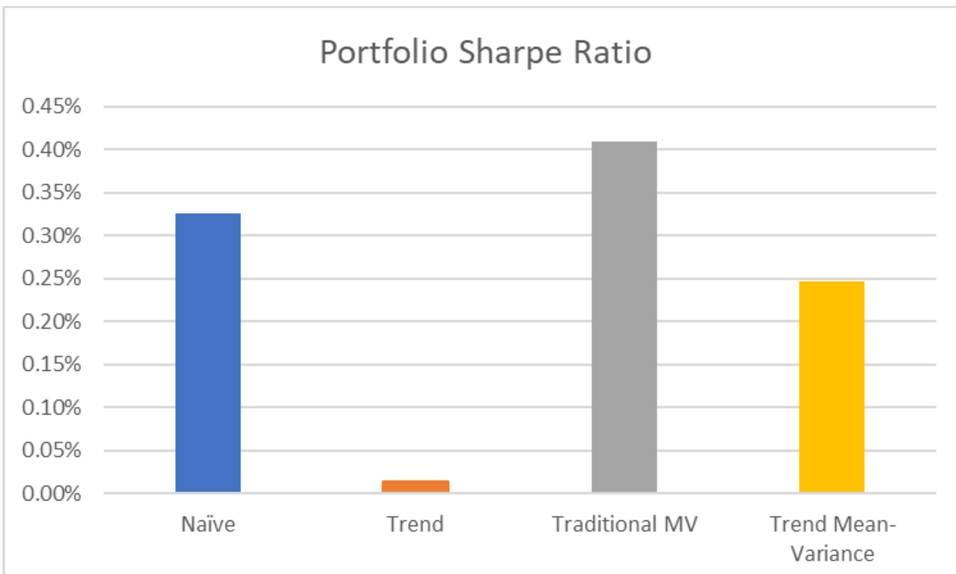


Figure 2 $10,000 Portfolio Model

Although it is great to look at the returns of a portfolio, in order to be an optimal portfolio, it has to have the highest Shape ratio. In Figure 3, the Sharpe ratio's of each portfolio was observed. The Naïve portfolio may have had the highest return, the Sharpe ratio illustrates which portfolio would perform the best if allowed to leverage debt at the risk free rate. The returns of the Traditional Mean-Variance portfolio, in combination with the smoothness seen in Figure 2 from the standard deviation shown in Figure 3, create an asset where debt without much risk of default. Note that the Trend Mean-Variance portfolio ranks third as far as Sharpe ratio is concerned. This doesn't seem right because of the smoothness seen in Figure 2 similar to the Traditional Mean-Variance. The hike of returns in the first few years followed by lower returns after 2013 can explain why, although having greater return than the Traditional Mean-Variance portfolio, it under performed in Sharpe ratio. The Naïve portfolio, although much more volatile than the other portfolios, has a higher Sharpe ratio than the Trend Mean-Variance portfolio because of its comparative high returns.



	Naïve	Trend	Traditional MV	Trend Mean-Variance
Mean Return	0.88%	0.06%	0.52%	0.55%
St. Dev.	2.71%	4.18%	1.26%	2.22%
Sharpe	0.33%	0.01%	0.41%	0.25%

Figure 3 Sharpe Ratio Information

Portfolio Significance

In order to test whether or not each portfolio's performance was statistically significant, I evaluate the Fama-French three factor alpha for each portfolio. To do this, the portfolio was regressed over the Fama-French model and the Alpha and its statistical significance can be seen in Figure 4. The Naïve portfolio has an alpha of 0.15% meaning that outside of the three factors in the FF model, the Naïve portfolio returns an excess 0.15% return.

This return however, is statistically insignificant with a p-value of .1894 which means there is an 18.94% chance that the alpha happened by chance. Within the Naïve portfolio, each of the three FF factors correlate heavily with the the Naïve portfolio with a total R Square of 82%. This means that the majority of the returns explained by the Naïve portfolio come from the factors within the Fama-French model. The Trend portfolio had a negative, statistically significant alpha showing that the method underperforms the three factors not by chance. This can be explained away by how the Trend portfolio created does not fit the normal Trend portfolio used by practitioners.

The Traditional Mean-Variacne portfolio has both the highest alpha and the highest statistical significance with an alpha of 0.22% and a p-value of .0106. Over half, 54%, of its returns are explainable by the Fama-French factors, the most statistically significant factors being a statistically significant negative relationship with the high book-to-value assets and the market risk free rate. The Trend Mean-Variance portfolio has an alpha of 0.09% and a p-stat of .6102 meaning the alpha has no statistical difference from the FF model. It shares the same statistically significant relationship between the FF models as the Traditional Mean-Variance portfolio and has an R Square of 41% showing that less then half of the returns are explainable by the FF model.

	Regression Significance Against Fama-French Model			
	Naïve	Trend	Traditional MV	Trend Mean-Variance
Alpha (Intercept)	0.15%	-0.78%	0.22%	0.09%
Alpha Significance (P-Stat)	18.94%	1.54%	1.06%	61.02%

Figure 4 Alpha Over Fama-French

Conclusion

Within the world of financial portfolio creation, practitioners and analysts alike are looking to find a portfolio creation method capable of achieving the highest amount of return over risk ratio. There are many different theories out their each with their own merits and disadvantages. The two addressed within this paper were trend analysis and mean-variance optimization. Within these two methods, there is the possibility some parts of one method in combination with information provided by the other may prove beneficial in creating a better return over risk performing portfolio. This research failed to prove any statistically significant benefit that combining the two methods could potentially have in the creation of a portfolio which rebalances yearly in six common mutual funds. The overall return of the Naïve Portfolio outperformed any other method within the study but did not have the best

Sharpe ratio, this was achieved by the Traditional Mean-Variance Portfolio. This result is, however, is partially the result of some limitations as well as suggestions for future research.

The biggest limitation faced in the research was due to a lack of software and computing power capable of processing a portfolio rebalance strategy shorter than one year. Due to the lack of computational abilities, this analysis was conducted based on a strict yearly rebalancing, even though trend portfolios most commonly rebalance the moment the trend switches in any asset. This not only explains the poor performance of the trend portfolio, but could also go to explain the insignificant difference of the trend covariance portfolio. Hypothetically, the change in covariance could be calculated and the portfolio could be rebalanced in the moment in which the trend shifts. This could allow for better performance if the trend happens to change midway through the year.

Another factor to be taken into consideration is the length of historical data used in covariance matrix calculations. In order to keep the research manageable for an undergraduate research assignment working in excel, the study showed data from 2009-2019. When calculating the initial covariances of both the Traditional Mean-Variance and Trend Mean-Variance portfolios of 2009, only the data from the year 2009 was used, but the covariances from 2019 spanned 2009-2019. Although more data could be beneficial, too much data can also be unrealistic. Using just the information from a single year might not make sense, but using the information since the day the stock originated may make equally little sense. If this study were to be improved upon, consider using all trend information ten years prior to the day the covariance is being evaluated when constructing a new matrix.

A third area to consider is the span of time the analysis covers. This analysis covered the years 2009-2019 which is only ten years of information. This means there are only ten data points used to test the significance of the covariance and ten years for the portfolios to prove their performance capabilities. In order to have a better idea about the significance of the covariance as well as the performance of a portfolio, it would make more sense to run an analysis looking over the span of 30 years. This length of time would be more suited for any portfolio created to save for retirement, which is a practical need for most people who invest.

The final factor to consider is whether each of the four trend relationships between two stocks has their own significant impact on covariance. This study assumes that the difference of the covariance of each of the four trend relationships for a set of two assets (1,1; 1,0; 0,0; 0,1) should be tested for significance against the covariance of all relationships as a whole. This makes sense for the purposes of analyzing the performance of the portfolio, but not so much in studying the significance of each individual relationship. In reality, it would make more sense to see if there is a statistically significant difference between each trend relationships.

This research offers guidance into what direction portfolio creation should go. The analysis provided proves that the Naïve Portfolio can get a great return over any other option and shows that, if looking to maximize the risk taken for the reward you get, the Mean-Variance portfolio is the way to go. Although the strategy being tested proved insignificant in this study, the suggestions offered within could lead to a clearer answer as to the impact of trends on covariance and information on a better performing portfolio.

Appendices

Appendix I (Naïve Regression)

SUMMARY OUTPUT									
Regression Statistics									
Multiple R	0.90908598								
R Square	0.82643732								
Adjusted R Square	0.82194863								
Standard Error	0.011489824								
Observations	120								
ANOVA									
	df	*SS*	*MS*	*F*	*Significance F*				
Regression	3	0.072918597	0.024306199	184.1154811	6.09263E-44				
Residual	116	0.015313862	0.000132016						
Total	119	0.08823246							
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*	
Intercept	**0.001463004**	0.001108243	1.320111374	**0.189396881**	-0.00073201	0.003658018	-0.00073201	0.003658018	
MKTRF	**0.643136416**	0.0304567	21.11641836	**1.50049E-41**	0.582813084	0.703459748	0.582813084	0.703459748	
SMB	**0.100868219**	0.050488122	1.997860389	**0.048071625**	0.000870132	0.200866306	0.000870132	0.200866306	
HML	**-0.180915783**	0.046670257	-3.876468543	**0.000176114**	-0.273352108	-0.088479459	-0.273352108	-0.088479459	

Appendix II (Trend Regression)

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.654778176							
R Square	0.42873446							
Adjusted R Square	0.413960351							
Standard Error	0.032771905							
Observations	120							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	3	0.093500025	0.031166675	29.01931116	4.51321E-14			
Residual	116	0.124583739	0.001073998					
Total	119	0.218083765						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.007774461	0.00316099	-2.459501772	0.015388396	-0.0140352	-0.001513722	-0.0140352	-0.001513722
MKTRF	0.736761391	0.086870267	8.481168694	8.28568E-14	0.564703881	0.908818901	0.564703881	0.908818901
SMB	0.071955866	0.144004986	0.499676209	0.61824956	-0.213264154	0.357175886	-0.213264154	0.357175886
HML	-0.2761993	0.133115463	-2.074885171	0.040208694	-0.539851247	-0.012547353	-0.539851247	-0.012547353

Appendix III (Traditional Mean-Variance Regression)

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.741448462							
R Square	0.549745821							
Adjusted R Square	0.538101317							
Standard Error	0.00859159							
Observations	120							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	3	0.010454644	0.003484881	47.2107521	5.13541E-20			
Residual	116	0.008562588	7.38154E-05					
Total	119	0.019017233						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.002153229	0.000828696	2.598335248	0.010582622	0.000511893	0.003794565	0.000511893	0.003794565
MKTRF	0.22937399	0.022774194	10.07166237	1.59695E-17	0.18426683	0.274481151	0.18426683	0.274481151
SMB	-0.049410894	0.037752819	-1.308800137	0.193189039	-0.124185109	0.02536332	-0.124185109	0.02536332
HML	-0.248671059	0.034897986	-7.125656512	9.4177E-11	-0.317790917	-0.179551201	-0.317790917	-0.179551201

Appendix IV (Trend Mean-Variance Regression)

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.643534178							
R Square	0.414136238							
Adjusted R Square	0.398984589							
Standard Error	0.017252							
Observations	120							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	3	0.024405264	0.008135088	27.3327502	1.91803E-13			
Residual	116	0.034525256	0.000297632					
Total	119	0.05893052						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.000850708	0.001664029	0.511233641	0.610159176	-0.002445112	0.004146527	-0.002445112	0.004146527
MKTRF	0.388186521	0.045730814	8.488511069	7.96913E-14	0.297610881	0.47876216	0.297610881	0.47876216
SMB	-0.036252119	0.075808046	-0.47820938	0.633401202	-0.186399506	0.113895269	-0.186399506	0.113895269
HML	-0.189776984	0.070075512	-2.708178341	0.007789364	-0.328570366	-0.050983603	-0.328570366	-0.050983603

Appendix V (Difference Regression)

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.43981407
R Square	0.193436416
Adjusted R Square	0.172577013
Standard Error	0.013221744
Observations	120

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0.004863345	0.001621115	9.273343806	1.51315E-05
Residual	116	0.020278484	0.000174815		
Total	119	0.02514183			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-0.001302521	0.001275294	-1.021349959	0.309214006	-0.003828401	0.001223359	-0.003828401	0.001223359
MKTRF	0.15881253	0.035047595	4.531338871	1.43273E-05	0.089396352	0.228228709	0.089396352	0.228228709
SMB	0.013158776	0.058098457	0.226490968	0.821218212	-0.101912538	0.12823009	-0.101912538	0.12823009
HML	0.058894075	0.053705105	1.096619669	0.275079041	-0.047475653	0.165263803	-0.047475653	0.165263803

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